

Performance Analysis of Adaptive Filtering Algorithms for Acoustic Echo Cancellation

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Abstract— The design of an efficient and robust hands-free system is now required by the growth of mobile radio and teleconference communications. For high quality acoustic echo cancellation long echoes have to be suppressed. This suppression of long echoes in acoustic echo cancellation shall be achieved by implementing frequency domain adaptive filtering algorithms. In this paper the time domain and frequency domain adaptive filtering algorithms are simulated and they are compared based on the convergence rate and echo return loss enhancement.

Keywords—Acoustic Echo Cancellation, Frequency Domain Adaptive Filtering, Echo Return Loss Enhancement

I. INTRODUCTION

Acoustic echo cancellation (AEC) is generally necessary in full-duplex communication scenarios where loudspeaker echoes should be removed from a microphone signal. This is necessary for teleconferences where the microphone signal is sent to far-end communication partners who may be disturbed when hearing their own voices. Adaptive filters designed for acoustic echo cancellation schemes are confronted with several difficulties. First, the number of taps needed to model the impulse response of an acoustic echo path shall be very large. Moreover, non stationary signals such as speech signals are highly correlated also the signal picked up by the microphone is corrupted by the near-end speech, and by the ambient noise. Dealing with long impulse responses, and designing adaptive filtering algorithms for highly correlated speech signals, has led to many time domain and frequency domain algorithms developed.[2,6] Here we have simulated the adaptive filtering algorithms in the time and frequency domain and compared them from the point of view of convergence, by varying step size and the performance parameter i.e. echo return loss enhancement.

II. DATABASE AND BASELINE SYSTEM

Time Domain Adaptive Filtering Algorithms

There are many conventional algorithms developed for acoustic echo cancellation such as LMS, NLMS, PNLMS and Affine Projection to update the filter coefficients by varying the step size, the number of filter coefficients and the projection order. The LMS algorithm is the most successful and efficient algorithm in terms of convergence and the computational complexity. The basic LMS algorithm updates the filter coefficients after every sample. The time-domain Block-LMS algorithm is based on a block

updating procedure of the filter weights, instead of a sample-by-sample one. The gradient is therefore estimated on a block-by-block. A very important part of the algorithm is the updating of the filter coefficients which is based on the step size (μ). This step size is critical for the update and must be chosen accurately to ensure the filter convergence. Updating the filter coefficients is important because this governs how well the filter will converge to the desired response. Another element that has a key role in this convergence is the number of filter coefficients N . Intuitively the number of coefficients must at least equal the length of the impulse response of the unknown system. The error is defined as the difference between the actual and the desired response of the adaptive filter. But the drawback of the LMS algorithm is that the computational complexity increases as the length of the impulse response becomes very long. The computing power required simply becomes too high for efficient use. This problem is efficiently solved by implementing fast LMS algorithm.

LMS Algorithm

This algorithm adapts to a solution of minimizing mean-square error. This method is based on steepest-descent method. In this, the gradient of mean-squared error is found out with respect to h . [11] If $w(n)$ is the weight vector and $x(n)$ is the input signal of adaptive filter then, output $y(n)$ of the adaptive filter is given by $y(n) = w(n)^T x(n)$ and the error signal $e(n)$ is given by

$$e(n) = d(n) - y(n)$$

the weight update equation is given by

$$w(n+1) = w(n) + \mu e(n) x(n)$$

where μ is the step size which controls the convergence rate. If the value of μ is small, then the convergence time is more. So the selection of suitable value of step size is very important. This algorithm is very simple and only requires few numbers of additions and multiplications per iteration for an N -tap filter. It has low computational complexity and the problem of double-talk is removed. But the step size chosen during every iteration in this method is of fixed size. The computational complexity of this algorithm involves $N+1$ additions and N^2 multiplications.[13]

NLMS Algorithm

Basically, this algorithm is an extension of LMS. This method[11] achieves faster convergence in time-domain as compared to frequency domain. Also, it has less complexity than LMS algorithm. It uses the weight update equation as

$$w_{(n+1)} = w_n + \mu \left[\frac{x(n)}{(x(n))^2} \right] e(n)$$

where μ is step size. Though the normalization of step size by $(n)^2$ diminishes the noise amplification problem, even then the problem occurs when (n) becomes too small. Therefore, the NLMS algorithm is modified as

$w_{(n+1)} = w_n + \mu x(n)\epsilon + x(n) 2\epsilon(n)$ where ϵ is a small positive number. [13] This converges faster than LMS algorithm because it uses time varying step size calculation, but its computational complexity is high. The computational complexity of this algorithm is $N(N+1)$ additions and N^2 multiplications.

Affine Projection Algorithm

The affine projection (AP) algorithm was proposed to speed up the convergence, which produces a good tradeoff between the convergence speed and the complexity.[12] When the projection order P increases, the convergence rate of the AP algorithm is improved at the price of a considerable rise of the computational complexity. The complexity of the direct calculation of the error vector is proportional to the projection order. The update equation of the AP algorithm is $\epsilon(n) = [\epsilon_0(n), \epsilon_1(n), \dots, \epsilon_{p-1}(n)]^T$
 $= \mu [X(n)X(n) + \delta I]^{-1} e(n)$

$w(n) = w(n-1) + X(n)e(n)$ where μ is the step size, and δ is a regularization parameter.

The PNLMS and IPNLMS algorithms were well suited for the sparse impulse responses of the hybrid echoes in the telephone system, but were not efficient for the long non sparse impulse responses with increased computational complexity such as in acoustic echo cancellation or hands free system introduced.[13]

Frequency Domain Adaptive Filtering Algorithms

The representation in the frequency domain of any signal is an alternative representation. The signals are represented in the frequency domain with the use of discrete transforms to reduce the processing required for signal processing applications. The Fourier Transform is the most widespread. The FFT [10] is used to minimize the number of calculations required and therefore make the algorithm more efficient. In acoustic echo cancellation frequency-domain adaptive filter (FDAF) algorithm is commonly used to improve the computational efficiency and the convergence rate[1].

For high quality acoustic echo cancellation long echoes have to be suppressed. Acoustic echo paths are characterized by FIR filters with lengths up to 250 ms. The FDAF is a block based adaptive filter which is a direct translation of block LMS[2] to the frequency domain. But this FDAF algorithm is

computationally efficient if the length of the block is same as the length of the filter. [6] But practically this same length is not possible and the algorithm leads to fast convergence rate with cost of more computational complexity of $N(N-1)$ complex additions and N^2 complex multiplications.

To overcome this problem the partitioned block frequency domain adaptive filtering algorithm[3,9] is suggested in which the length of the filter is partitioned into equal length blocks and transformed into frequency domain. The overall performance of the FDAF algorithm is highly influenced by the choice of the step-size parameter,[4] i.e. a large value

leads to fast convergence rate but a high sensitivity to local speech disturbance, and vice versa.

III. IMPLEMENTATION

This framework consists of various acoustic inputs with different lengths considered and the adaptive filters using various algorithms are simulated using Matlab. Firstly, the acoustics of the loudspeaker-to-microphone signal path are described where the speakerphone is located. A room impulse response is generated which acts as the echo path. Then w. r. t. the input signal the adaptive filter updates its coefficients using different algorithms. The teleconferencing system's user is mainly located near the system's microphone which is called as near end speech signal. A voice travels out the loudspeaker, bounces around in the room, and this voice is picked up by the system's microphone; this voice signal is called as far end speech signal. The microphone signal contains both the near end speech and the far end speech that has been echoed throughout the room. The acoustic echo cancellation here is implemented using various acoustic inputs of long lengths up to 250 ms[5] with adaptive filter of length 2048 coefficients. The input signal is sampled at a rate of 8000Hz.

IV. PERFORMANCE PARAMETERS

The performance parameter which is used here for the performance evaluation of different AEC algorithms is as follow:

ERLE (Echo rate loss enhancement): It is a smoothed measure of the amount (in dB) that the echo has been attenuated. The ERLE used is given by, $ERLE = 10 \log_{10} \{ [d^2(n)] / E[e^2(n)] \}$

where $d(n)$ is the far-end echoed signal and $e(n)$ is the residual echo after cancellation.

Mean square error: It contains the sequence of mean-square errors. This column vector contains predictions of the mean-square error of adaptive filter at each time instant. The MSE is calculated as,

$$MSE = 1/N \sum_{k=1}^N e(k)^2$$

where N is the filter length and $e(k)$ is the error signal achieved at the output of filter.

V. SIMULATION RESULTS

Algorithm	Step size	ERLE in dB	Convergence time
FDAF	0.025	18	7.511 sec
Frequency Domain Adaptive Filter	0.04	19	
PBFDAF	0.006	25	7.249 sec
Partition Block FDAF	0.008	28	
UFDAF	0.025	10	5.586 sec
Unconstrained FDAF	0.04	12	
PBUFDAF	0.025	12	6.393 sec
Partition Block Unconstrained FDAF	0.03	08	
BLMSFFT	0.0004	08	5.342 sec
Block LMS Fast Fourier Transform	0.0009	10	
BAP	0.04	15	60.164 sec
Block Affine Projection	0.08	18	
BLMS	0.004	10	7.568 sec
Block Least Mean Square	0.009	12	
NLMS	0.025	12	15.60 sec
Normalized Least Mean Square	0.04	14	
LMS	0.002	10	13.75 sec
Least Mean Square	0.004	12	

Discussion:

The performance of all the algorithms is evaluated based on the Echo Return Loss Enhancement (ERLE) parameter as well as the required convergence time. The convergence and ERLE of the algorithms is observed by varying the step size of the algorithms. The fig 2 of PBFDAF algorithm shows the best rate of echo cancellation as the ERLE for this algorithm is 28 dB at the cost of more convergence time required as compared to other algorithms. We know that more the value of ERLE better is the rate of echo cancellation. Further by observing the convergence time of all algorithms the BLMSFFT in fig 5 converges faster than all other algorithms. The mean square error of all the algorithms is also reduced to zero. The FDAF, UFDAF, PBUFDAF and NLMS are simulated with same step size in which the FDAF of fig 1 has better ERLE and hence more efficient as compared to others. The simulated output of all these algorithms is shown below.

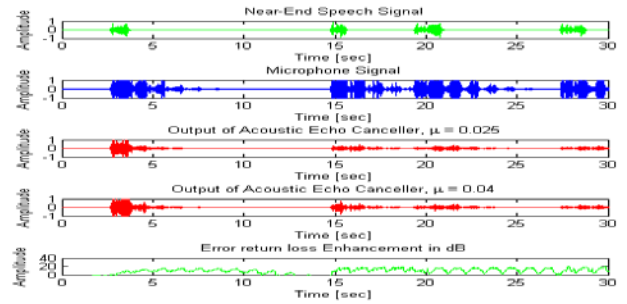


Fig 1 FDAF Algorithm

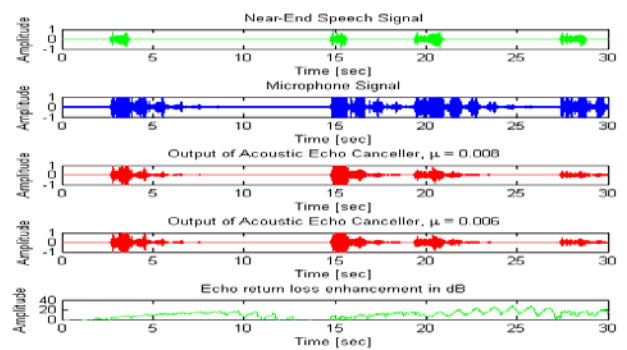


Fig 2 PBFDAF Algorithm

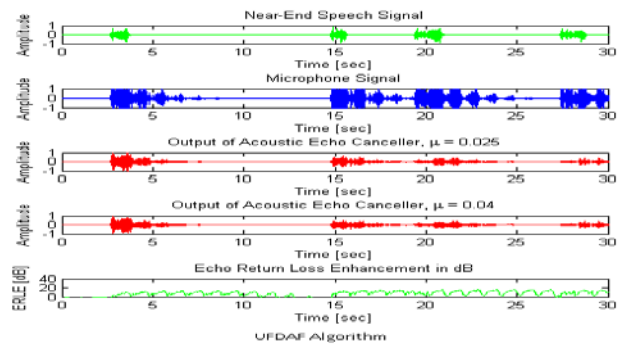


Fig 3 UFDAF Algorithm

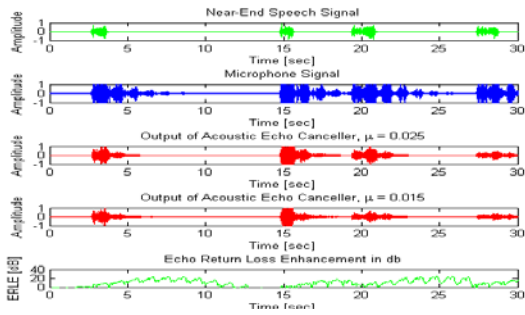


Fig 4 PBUFDAF Algorithm

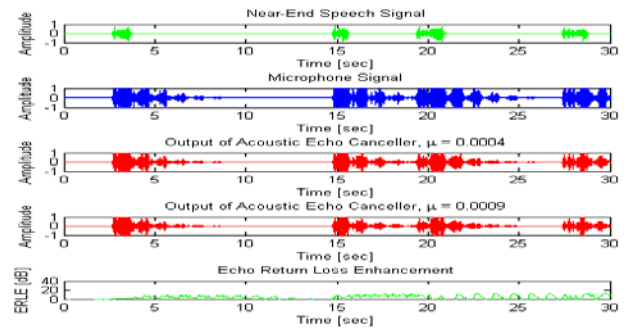


Fig 7 BLMS Algorithm

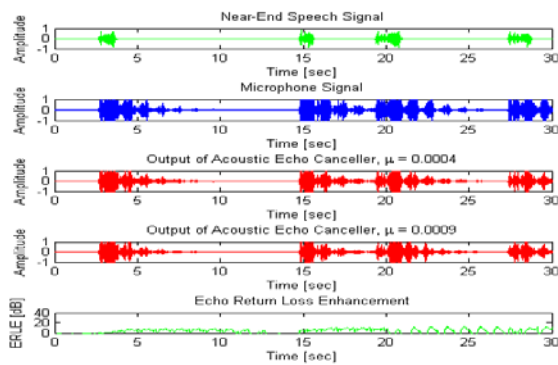


Fig 5 BLMSFFT Algorithm

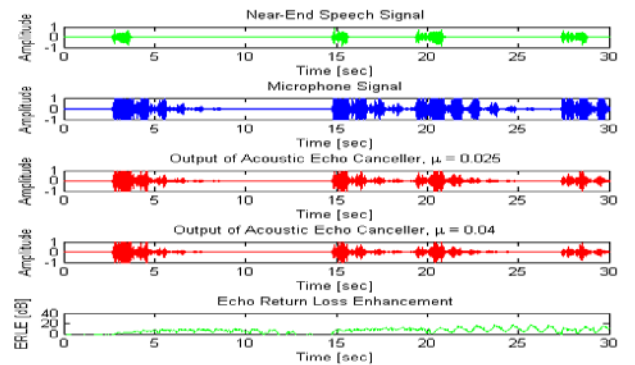


Fig 8 NLMS Algorithm

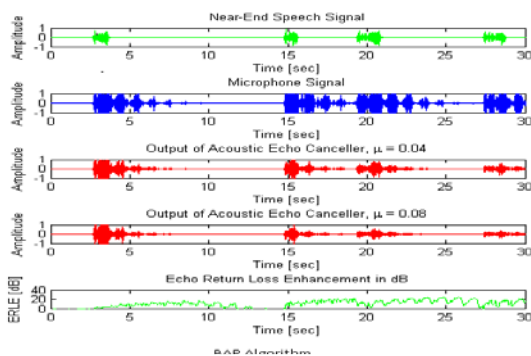


Fig 6 BAP Algorithm

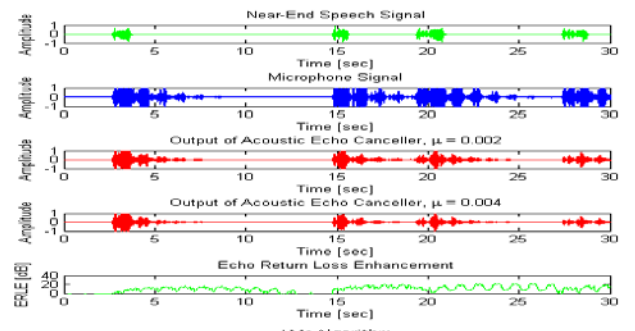


Fig 9 LMS Algorithm

The goal of adaptive echo canceller is to remove the far end echoed speech signal, so that only near end speech signal is transmitted back to the far-end listener. Since, we have access to both near end and far end speech signals, so echo return loss enhancement is also calculated, which is the amount(in dB) that how much echo has been attenuated. From the table it has been seen that approx. 30 dB ERLE is achieved at the end of convergence period using PBFDAF algorithm.

The table shows the ERLE achieved for different values of step sizes for the FDAF algorithm. It is clear from the results of table that if the value of filter length is constant & the value of step size is increased, then the amount of ERLE

achieved at the end of convergence period is decreased. So, PBFDAF algorithm works better for the filter length of 2048 with step size of 0.006 and 0.008.

VI. CONCLUSION

Based on the simulation results acoustic echo cancellation for long impulse responses can be achieved by implementing frequency domain adaptive filtering algorithms which are robust and outperforming with good echo return loss enhancement and improved convergence rate.

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VIII. REFERENCES

- [1] Acoustic Echo Cancellation and Noise Reduction in the Frequency-Domain: A Global Optimisation by F. Capman , J. Boudy , P. Lockwood Matra Communication, Speech Processing Department rue J.P. Timbaud, 78392 Bois d'Arcy Cedex, BP 26, France
- [2] The generalized frequency-domain adaptive filtering algorithm as an approximation of the block recursive least-squares algorithm by Martin Schneider* and Walter Kellermann EURASIP Journal on Advances in Signal Processing (2016)
- [3] The iterated partitioned block frequency domain adaptive filter for Acoustic Echo Cancellation by koen Eneman and Marc Moonen, Katholieke University Belgium.
- [4] A Robust variable step-size frequency-domain adaptive filter algorithm for acoustic echo cancellation by Feiran Yang, Ming Wu, Peifeng Ji, Jun Yang Key Laboratory of Noise and Vibration Research, Institute of Acoustics, Chinese Academy of Sciences, Beijing, China 100190,
- [5] Paez Borrello, GarciaOtero, On the implementation of partitioned block frequency domain adaptive filter for long acoustic echo cancellation, *Signal Processing*, 27,301:315, 1992.
- [6] Shynk, J.J., "Frequency-Domain and Multirate Adaptive Filtering," *IEEE® Signal Processing Magazine*, vol. 9, no. 1, pp. 14-37, Jan. 1992
- [7] R. L. A. Azpicueta uiz, A. R. Figueiras-Vidal, and J. Arenas-García, "Acoustic echo cancellation in frequency domain using combinations of filters," in 19th Int. Congress on Acoustics (ICA), Madrid, Sep. 2007.
- [8] So, J.S. and K.K. Pang, "Multi delay Block Frequency Domain Adaptive Filter," *IEEE® Trans. Acoustics, Speech, and Signal Processing*, vol. 38, no. 2, pp. 373-376, February 1990
- [9] Gerald Enzner, Peter Vary, "A soft-partitioned frequency-domain adaptive filter for acoustic echo cancellation,"*Proc. IEEE Conference on Acoustics, Speech and Signal Processing, (ICASSP 2003)*,Vol. 5, 2003, 393-396.
- [10] Mr. K. G. Gunale, Ms. S. N. Motade, Dr. S. L. Nalbalwar, "Frequency domain adaptive filter using FFT algorithm for acoustic echo cancellation," Third International Conference on Emerging Trends in Engineering and Technology, IEEE, 2010, 582-587.
- [11] Ms. Mugdha. M. Dewasthale, Dr. R. D. Kharadkar, "Acoustic noise cancellation using adaptive filters: A Survey,"*International Conference on Electronic Systems, Signal Processing and and Computing Technologies, Nagpur , India, Jan. 2014, 12-16.*
- [12] H. C. Shin, A. H. Sayed, and W. J. Song, "Variable step-size NLMS and affine projection algorithms," *IEEE Signal Processing Letters*, vol. 11, no. 2, pp. 132-135, Feb. 2004
- [13] Acoustic Echo Cancellation using Adaptive Algorithms by V.V.Sudhir; A S N Murthy; Dr.D Elizabeth Rani, *International Journal of Advances in Computer Science and Technology* Volume 3, No.4, April 2014
- [14] Adaptive Algorithms for Acoustic Echo Cancellation: A Review by Nitika Gulbadhar, Shalini Bahel, Harmeet Kau, *International Journal of Engineering Trends and Technology (IJETT) – Volume 34 Number 5- April 2016*